

A Review of the Application of Evolutionary Deep Learning in Solving the Multi-task Robot Manipulation Synergy Effect

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Abstract: As robot technology enters a new era, multi-task robot manipulation has entered high-quality development. Sticking to the people-oriented philosophy, people propose synergistic effects to better meet the complex environment and diverse needs. Based on the dynamic evolution of evolutionary deep learning, the researchers construct a theoretical analysis framework for the synergistic effect of multi-task robot manipulation according to the logic of adaptation, optimization, enhancement, and evaluation. It can explain the synergistic effect of collaborative learning and optimization mechanisms involving deep learning and evolutionary algorithms. Moreover, from the perspective of the actual changes and practices of multi-task robot manipulations, we explore the possibility of moving toward high-quality development. Multi-task robot manipulation aims to provide users with results that meet the expected standards and continuously improve operation quality and user satisfaction. Therefore, we should take measures such as strengthening the collaboration based on course learning, constructing the mechanism of the interaction mechanism and optimization between the evolutionary strategy and simulator, and establishing the collaborative effect evaluation system of the PILCO framework, realize the high-quality collaborative effect of multi-task robot manipulation, promote the development of robot technology and meet the needs of users.

Keywords: Evolutionary Deep Learning; Multi-task robot manipulation; Synergy Effect; High-quality development

1. Introduction

Evolutionary deep learning is a machine learning method that combines deep learning and evolutionary algorithms. It can adaptively optimize strategies and models in complex environments. Multi-task robot manipulation means the robot performs multiple related or unrelated tasks simultaneously, such as grasping, moving, stacking, etc. The synergy effect refers to the information sharing and complementarity between different tasks in multi-task robot manipulation, which can improve operational efficiency and quality. The application of evolutionary deep learning in solving the synergy effect of multi-task robot manipulation has been a hot and challenging point in robot technology in recent years.

Applying evolutionary deep learning to improve the synergy effect of multi-task robot manipulation involves many aspects of technology and challenges, such as designing appropriate network architecture, optimization methods, and task relationship learning. The network architecture determines the degree of information sharing and separation between different tasks; the optimization method influences how to balance the loss function and weight of different tasks; task relationship learning determines how to use the similarity and differences between tasks to improve the effect. They all need to consider the characteristics of multi-task robot manipulations, such as high-dimensional action and state space, data sampling efficiency, partial observability, and security.

This paper reviews the application of evolutionary deep learning in solving the synergy effect of multi-task robot manipulation. The main issues are summarized by analyzing existing theories and methods as prospects for future development directions. The main contents of this paper are as follows. The first part introduces the basic concepts and background of evolutionary deep learning, multi-task robot manipulation, and synergy effect. The second part introduces the main methods and techniques of evolutionary deep learning in solving the synergy effect of multi-task robot manipulation, including

network architecture, optimization method, and task relationship learning. The third part introduces the main problems and challenges in applying evolutionary deep learning in the synergy effect of multi-task robot manipulation, including data sampling efficiency, model generalization ability, and security. The fourth part outlines the future development for applying evolutionary deep learning to solve the synergy effect of multi-task robot manipulation, including model simplification, transfer learning, and meta-learning.

2. Research Background and Significance of Multi-task Robot Manipulation Synergy Effect

2.1 The Complexity and Diversity of Robot Manipulation

Robot manipulation is a concept that develops with robot technology. It embodies artificial intelligence, highlights the autonomy and flexibility of robots, and reflects the automation and intelligence strategies in the industrial field since the 20th century. However, it is still difficult to be unified and accurate when we use technical standards to discover the definition and essence of robot manipulation [1].

2.2 Challenges and Requirements for Multi-task Learning

Multi-task learning is an essential standard of machine learning and a representation of machine learning models' generalization ability and flexibility. Multi-task learning and single-task learning discuss definitions of machine learning from the perspectives of the objective function, data utilization, and model structure. In addition, some scholars consider that multi-task learning is an extension of single-task learning or a particular case of single-task learning. Multi-task learning is more challenging to some extent, which belongs to applied science aiming at solving practical problems. The research history of multi-task learning can even be traced back to the 1980s. Its principal activities include designing multi-task models, optimizing multi-task goals, and selecting appropriate auxiliary tasks. The concepts and applications of multi-task learning are closely related to the development of artificial intelligence. Through multi-task learning, artificial intelligence has become an essential tool for solving complex problems. The main contribution of the multi-task learning theory in deep learning is to propose a multi-task architecture and regularization technology based on deep neural networks. Therefore, the concept of multi-task learning initially focused on feature extraction based on data-sharing attributes.

2.3 Definition and Evaluation Method of Synergy Effect

Compared with other evaluation methods, the theoretical model of the synergy effect emphasizes the relationship between M&A strategy, resources, competition, and integration, which has high theoretical value and guiding value [2]. Although some scholars have questioned that synergies may not directly relate to M&A performance, most advocate that synergies can rationally evaluate M&A strategies. Ansoff et al. proposed a classical theoretical model containing the synergy effect of four elements. Since then, the model has become a standard tool for M & A strategy analysis, thus developing the concept of diversification strategy. Scholars believe the synergy effect is value-added, a phenomenon of “ $1 + 1 > 2$ ”. The synergy effect will appear only when the two sides of M & A can realize resource sharing, complementary ability, competitive advantage, and integration efficiency [3]. Therefore, the synergy effect is the result of successful merger and acquisition. In addition, some scholars summarized the synergy effect into the resource-based internal synergy model and the market-based external synergy model. The former focuses on resource integration and utilization, while the latter focuses on market expansion and competitive advantage with internal and external strengths. The synergy effect has experienced some practical failures, but from a theoretical point of view, it can provide a practical framework for assessing the value and risk of M&A strategy. Synergy theory has gradually become the consensus of M & A research and practice [4].

3. Theoretical Basis and Key Technologies of Evolutionary Deep Learning

3.1 Concepts and Categories of Evolutionary Deep Learning

Evolutionary deep learning combines deep learning and evolutionary computing, focusing on deep models' mechanical design and optimization. The evolutionary algorithm directly reflects the optimization of the structure and parameters of the depth model. Some components of evolutionary deep

learning development are gradually being formed, such as solution representation, search paradigm, and acceleration strategy. Moreover, various evaluation systems have gradually received attention. However, from the perspective of practical application, some practices of evolutionary deep learning remain in the stage of small-scale data sets or simple tasks, contrary to the logical framework and generation mechanism of deep learning. Therefore, problems such as computational efficiency, interpretability, and mobility are derived [5].

3.2 The Advantages and Limitations of Evolutionary Deep Learning

From the perspective of deep learning, evolutionary computation is the foundation and core embodiment of deep learning. Therefore, evolutionary deep learning takes evolutionary computing as the primary generation logic. Evolutionary computation is one of the main optimization methods of deep learning and is also the main innovation of deep learning. Currently, evolutionary deep learning strengthens model control from multiple perspectives. There are three primary forms: First, characteristic engineering. Apparent features realize information conversion between data and model; Second, model generation. By formulating the model structure and parameters and disclosing the model evaluation to users, the automatic control of the model is realized. Third, the internal deployment process reengineering of the model. In recent years, neural architecture search has used evolutionary computing to improve model performance and efficiency. However, compared with machine learning, the interpretability of evolutionary deep learning needs to be improved [6].

3.3 The Main Algorithms and Frameworks of Evolutionary Deep Learning

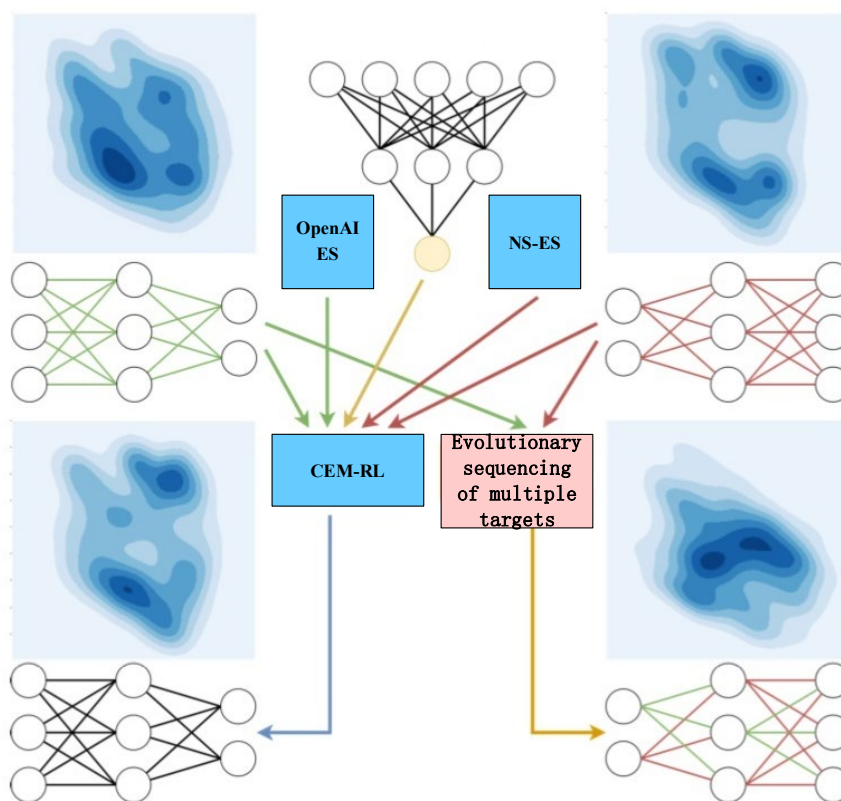


Figure 1: Evolutionary deep learning algorithm framework

The deep generative model is used to project molecular structure or other data from discrete space to continuous space, where evolutionary operations such as selection, crossover, and mutation are applied to explore potential space. From the algorithm perspective, evolutionary deep learning is the optimization and innovation of deep learning. Therefore, evolutionary deep learning takes evolutionary computing as the main optimization logic. Evolutionary computation is the framework foundation of deep learning. Evolutionary deep learning constructs algorithms and frameworks from three perspectives at this stage. There are three primary forms: First, the evolutionary operation is based on potential space. The deep generative model is used to project molecular structure or other data from discrete space to continuous

space, where evolutionary operations such as selection, crossover, and mutation are applied to explore potential space. The second is evolutionary ranking based on multi-objective, by setting multiple properties or attributes as optimization objectives and using non-dominated sorting and crowding distance to achieve multi-objective balanced optimization. The third is model fine-tuning based on data augmentation. Specifically, the new samples generated during the evolution process enrich the training data. The model is generated for fine-tuning to improve the generalization ability and generation quality of the model. In recent years, OpenAI ES, NS-ES, CEM-RL, etc., all use evolutionary deep learning as the core idea to improve performance and efficiency [7]. However, compared with traditional optimization methods, the computational complexity of current evolutionary deep learning needs to be reduced. The main framework is shown in Figure 1.

4. The Application of Evolutionary Deep Learning in the Synergy Effect of Multi-task Robot Manipulation

4.1 Multi-task Robot Manipulation Synergy Enhancement Method Based on Course Learning

From the perspective of robot learning, the synergy effect of multi-task robot operation is that multiple robots' complete complex operation tasks, such as handling, assembly, and exploration, through communication and cooperation. The enhancement method of multi-task robot operation synergy refers to improving the coordination and collaboration between robots to improve the efficiency and quality of execution. The multi-task robot operation collaborative enhancement method based on course learning is effective. Its basic idea is to imitate the learning process of human beings so that robots begin to learn from simple tasks and gradually advance to complex tasks. The advantages of course learning include that it can reduce the difficulty of training, accelerate the convergence speed, improve the generalization ability, and avoid local optimization.

In this section, the challenge in course learning is how to design the appropriate course, that is, how to determine the task's difficulty and arrange the order and proportion of tasks. Currently, there are mainly two curriculum design methods: predefined courses and automatic courses. The predefined courses are divided and sorted according to artificially set rules or standards, including task complexity, reward, data volume, etc. Automatic courses are based on data-driven or model feedback to dynamically adjust the difficulty and order of tasks, such as self-paced learning, transfer teachers, and reinforcement learning teachers. The automatic course has better flexibility and adaptability for the multi-task robot manipulation synergy effect. The optimal course can be formulated according to the characteristics of robots and environments [8].

The key issues are enhancing the synergistic effect of multi-task robot manipulation based on course learning, accurate evaluation of task difficulty, practical design of training schedules, and practical information exchange and cooperation. There are still some problems in this field, such as the need for standard evaluation data sets and indicators, imperfect theoretical analysis, and the efficiency and robustness of the algorithm need to be improved. Therefore, we must study further and explore more algorithms and application scenarios.

4.2 Optimization Method of Multi-task Robot Manipulation Synergistic Effect Based on Evolutionary Strategy

From the perspective of robot cooperation, communication cost, and coordination strategies have long restricted the ability of multi-task robots' synergistic effects. Since the 20th century, integrating evolutionary algorithms and reinforcement learning has reshaped multi-task robot operation collaboration through adaptive optimization. However, the drawbacks of traditional evolutionary strategies still restrict the synergistic effect. Because of the complexity of the sample and the influence of environmental dynamics, the evolutionary strategy needs to be improved. Under the premise of distributed computing, the multi-task robot manipulation synergy optimization based on evolutionary strategy is regarded as a direct way to improve efficiency and quality. However, the practical effect of evolutionary strategy based on fitness function on collaboration remains to be discussed. In addition, due to communication bandwidth and delay, multi-task robots lack effective information exchange and cooperation strategies. Therefore, optimizing multi-task robot manipulation synergy based on an evolutionary strategy does not consistently achieve the goal. It is concluded that the synergy effect of multi-task robot manipulation is a technical problem, and the problem of communication and coordination should be solved.

4.3 Data Augmentation Method of Multi-task Robot Manipulation Synergy Based on Simulator

The synergy effect of multi-task robot manipulation cannot avoid 'data hunger' in improving robot intelligence and autonomy. In the machine learning mechanism, data is a standard and effective training tool that is important in improving model performance, making data not only a technical concept but also a strategic one. Therefore, the method based on data augmentation has become the core mechanism of multi-task robot operation coordination. The practice of data augmentation is generally an incremental expansion path based on actual environmental data, although this path contains various technical attempts. From traditional data transformation to data augmentation based on simulator-based multi-task robot manipulation synergy, data augmentation has always been closely connected with improving data quality and quantity. The simulator-based approach should improve the consistency between the simulator and the natural environment to meet the complex and changing needs. However, the simulator's attention also brings a dilemma: the simulation-reality gap phenomenon. There is room for improvement in data augmentation of multi-task robot manipulation synergy effect based on the simulator in improving simulation accuracy, reducing calculation cost, and ensuring safety. The evaluation criteria also need to be improved, which is also the focus of multi-task robot manipulation synergy research.

5. Conclusions

The synergy effect of multi-task robot manipulation has become a hot issue in robotics, which poses new challenges and requirements for improving the intelligence and autonomy of robots. The synergy effect of multi-task robot manipulation symbolizes robot efficiency and an essential means to improve working quality and efficiency. In addition, it reflects the urgent need for robot intelligence and maintenance of the stability of the robot crowd. In essence, it embodies the inherent requirements of robot learning. The synergy effect enhancement of multi-task robot manipulation based on course learning, evolutionary strategy, and simulator is to construct a theoretical analysis framework and practical mechanism of synergy effect under the guidance of data-driven and adaptive optimization. In recent years, modern information technologies such as deep learning and reinforcement learning have promoted the development of multi-task robot manipulation synergy. Through data augmentation and model training, people can empower the multi-task robot manipulation synergy effect and the accuracy and scientific nature of the coordination. Its value fits the internal logic of robot learning. Therefore, the method based on course learning, evolutionary strategy, and simulator provides a new path for the synergy effect of multi-task robot manipulation. To sum up, the sustainable improvement and development of the multi-task robot manipulation synergy effect will help improve robots' intelligence and autonomy and promote innovation for robots.

References

- [1] Nguyen H, La H. Review of deep reinforcement learning for robot manipulation[C]//2019 Third IEEE International Conference on Robotic Computing (IRC). IEEE, 2019: 590-595.
- [2] Adegboye A, Ojeka S A, Tolase O, et al. Technology penetration and human development nexus in middle-income countries: the synergy effect of inclusive resources distribution [J]. *Information Technology for Development*, 2022, 28(4): 860-874.
- [3] Lee R, Lee J H, Garrett T C. Synergy effects of innovation on firm performance[J]. *Journal of Business Research*, 2019, 99: 507-515.
- [4] Ge G, Cheng X, Liao M, et al. A review of the synergy effect in multi-break VCBs [J]. *IEEE Transactions on Plasma Science*, 2018, 47(1): 671-679.
- [5] Camero A, Toutouh J, Stolfi D H, et al. Evolutionary deep learning for car park occupancy prediction in smart cities[C]//Learning and Intelligent Optimization: 12th International Conference, LION 12, Kalamata, Greece, June 10–15, 2018, Revised Selected Papers 12. Springer International Publishing, 2019: 386-401.
- [6] Ghoniem R M, Algarni A D, Refky B, et al. Multi-modal evolutionary deep learning model for ovarian cancer diagnosis [J]. *Symmetry*, 2021, 13(4): 643.
- [7] Fujino S, Hatanaka T, Mori N, et al. Evolutionary deep learning based on deep convolutional neural network for anime storyboard recognition[J]. *Neurocomputing*, 2019, 338: 393-398.
- [8] Shridhar M, Manuelli L, Fox D. Perceiver-actor: A multi-task transformer for robotic manipulation [C] // Conference on Robot Learning. PMLR, 2023: 785-799.